An Overview of Space-Time Adaptive Processing for Radar

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Abstract —**This paper provides a survey of space-time adaptive processing for radar target detection. Specifically, early work on adaptive array processing from the point of view of maximum signal-to-noise-ratio and minimum mean squared error perspectives are briefly reviewed for motivation. The sample matrix inversion method of Reed, Mallet and Brennan is discussed with attention devoted to its convergence properties. Variants of this approach such as the Kelly GLRT, adaptive matched filter and ACE tests are considered. Extensions to handle the case of non-Gaussian clutter statistics are presented. Current challenges of limited training data support, computational cost, and severely heterogeneous clutter backgrounds are outlined. Implementation and performance issues pertaining to reduced rank and model-based parametric approaches are presented.**

I. INTRODUCTION

Signal detection using an array of sensors has offered significant benefits in a variety of applications such as radar, sonar, satellite communications, and seismic systems. Employing an array of sensors overcomes the directivity and beamwidth limitations of a single sensor. Additional gain afforded by an array of sensors leads to improvement in the Signal-to-Noise-ratio, resulting in an ability to place deep nulls in the direction of interfering signals. Finally, a system using an array of sensors affords enhanced reliability compared to a single sensor system. For example, sensor failure in a single sensor system leads to severe degradation in performance whereas sensor failure in an array results in graceful performance degradation.

A problem of considerable importance in this context is the adaptive radar detection of desired targets against a background of interference consisting of clutter, one or more jammers and background noise. The radar receiver front end consists of an array of antenna elements. The received signal is an electromagnetic plane wave impinging on the array manifold. The electromagnetic plane wave induces a voltage at each element of the array, which constitutes the measured data. Several snapshots of measured data are available in practice. Using the snapshots of data, the problem at hand is to detect desired targets in the presence of interfering signals. An important requirement is that of a constant probability of false alarm. In practice, the interference statistics, the interference spectral characteristics, and the target complex amplitude are unknown. Thus, the problem of adaptive radar target detection in interference is equivalent to the problem of statistical hypothesis testing in the presence of nuisance parameters. Present day computing power permits the use of well-known tools from statistical detection and estimation theory in the radar problem. The Doppler-Wavenumber or angle Doppler spectrum provides a unique representation of a signal in a three dimensional plane. Hence, the problem of space-time adaptive processing (STAP) may also be viewed as a spectrum estimation problem where the two-dimensional Fourier transform of spatio-temporal data affords separation of the desired target from interference. This scenario is described in Figure 1.

II. STAP OUTLINE

Typically, a radar transmits a burst of N pulses in a coherent processing interval. The data measured at the array thus consists of a JNx1 complex valued vector, where J is the number of elements in the array. This corresponds to N snapshots obtained from the J element array. Furthermore, since most radars employ a high pulse repetition frequency (PRF), there is a temporal correlation between successive pulses at a given element of the array. Furthermore, the array geometry introduces an element-to-element spatial correlation as shown in Figure 2. Thus in the context of STAP, the unknown interference spectral characteristics correspond to the unknown spatio-temporal correlation or covariance matrix of the JNx1 complex-vector under the condition that the data consists of interference alone. Additionally, interference statistics can be either Gaussian or non-Gaussian. In the latter case, all STAP methods would be based on a suitable model for the interference statistics.

The presence of unknown parameters in the problem precludes the use of a uniformly most powerful test for the adaptive target detection problem. This is due to the fact that joint maximization of a likelihood ratio over the domain of unknown parameters is extremely difficult. Hence, ad hoc approaches have been proposed to overcome this problem. Most of the work in the area of STAP is based on the Gaussian model for the interference. STAP for non-Gaussian interference has received increased attention in recent times.

Succinctly stated, most classical STAP algorithms consist of the following steps depicted in Figure 3.
(i) Estimate nuisance parameters (interference covariance matrix and target complex amplitude)

0-7803-7871-7/03/$17.00 © 2003 IEEE

Report Documentation Page

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1. REPORT DATE **14 APR 2005**	2. REPORT TYPE **N/A**	3. DATES COVERED **-**

4. TITLE AND SUBTITLE **An Overview of Space-Time Adaptive Processing for Radar**	5a. CONTRACT NUMBER
	5b. GRANT NUMBER
	5c. PROGRAM ELEMENT NUMBER
6. AUTHOR(S)	5d. PROJECT NUMBER
	5e. TASK NUMBER
	5f. WORK UNIT NUMBER
7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES) **Air Force Research Laboratory/SNHE Hanscom Air Force Base, MA, USA**	8. PERFORMING ORGANIZATION REPORT NUMBER
9. SPONSORING/MONITORING AGENCY NAME(S) AND ADDRESS(ES)	10. SPONSOR/MONITOR'S ACRONYM(S)
	11. SPONSOR/MONITOR'S REPORT NUMBER(S)

12. DISTRIBUTION/AVAILABILITY STATEMENT
Approved for public release, distribution unlimited

13. SUPPLEMENTARY NOTES
See also ADM001798, Proceedings of the International Conference on Radar (RADAR 2003) Held in Adelaide, Australia on 3-5 September 2003., The original document contains color images.

14. ABSTRACT

15. SUBJECT TERMS

16. SECURITY CLASSIFICATION OF:			17. LIMITATION OF ABSTRACT	18. NUMBER OF PAGES	19a. NAME OF RESPONSIBLE PERSON
a. REPORT **unclassified**	b. ABSTRACT **unclassified**	c. THIS PAGE **unclassified**	**UU**	**6**	

Standard Form 298 (Rev. 8-98)
Prescribed by ANSI Std Z39-18

(ii) Form a weight vector based on the inverse covariance matrix
(iii) Calculate the inner product of the weight vector and the data vector from a cell under test
(iv)Compare the squared magnitude of the inner product in step (iii) with a threshold determined according to a specified false alarm probability.

Several interesting theoretical interpretations have been offered for the STAP algorithms in the literature. However, from a practical standpoint the key issues include:

(I) Sufficient target-free training data support to form an estimated interference covariance matrix.
(II) Non-singular estimated covariance matrix to form the weight vector.
(III) Computational complexity in forming the weight vector.
(IV) The ability to maintain a constant false alarm rate (CFAR) and robust detection performance.

III. IMPLEMENTATION ISSUES

Early work in the 1960s by Widrow [1] (least squares method), Applebaum [2] (maximum signal-to-noise-ratio criterion) and Howells [3] (sidelobe canceller) suggested the use of feedback loops with an appropriate error criterion to control the convergence of iterative methods for calculating the weight vector in adaptive arrays. However, these methods were slow to converge to the steady-state solution. Fundamental work by Reed, Mallet and Brennan [4] (RMB beamformer) in 1974 showed that the sample matrix inverse method offered considerably better convergence properties compared to the work of Widrow et. al. Key requirements of the RMB beamformer are the availability of at least JN training data vectors for forming the sample covariance matrix and the availability of 2JN training data vectors to achieve performance within 3 dB of the optimal SNR. Computational complexity of the RMB method is $O(M^3)$ where M=JN. A drawback of the RMB approach is the lack of CFAR. Modifications and extensions of this approach to obtain CFAR was the focus of a number of efforts in the 1980s and early 1990s. These resulted in a number of algorithms such as the Kelly-GLRT[5], the adaptive matched filter [6,7], and the adaptive coherence estimator [8-13]. However, training data requirements and computational complexity of the algorithms remain unchanged from that of the RMB beamformer. Performance of all sample covariance based STAP methods degrade in heterogeneous [14-17] and non-Gaussian interference scenarios [18-20]. In the latter case, this is due to the fact that the sample covariance matrix suffers from significant estimation errors [21-23]. Consequently, a much larger training data support (compared to the Gaussian case) is needed.

On the other hand, collecting sufficient training data depends on system considerations such as bandwidth, frequency agility, and range extent as well as environmental conditions such as the non-homogeneity and non-stationarity of the scanned areas. These factors preclude the collection of large amounts of training data. The problem can become severe with increasing dimensionality. For example, 10 snapshots of data collected from a 32 element antenna array gives rise to the problem of estimating a 320x320 covariance matrix. Using the rule of the RMB beamformer, this necessitates the use of 640 target-free training data vectors to estimate the covariance matrix. Assuming an instantaneous RF bandwidth of 200 KHz, the representative training data assumption calls for wide sense stationarity to prevail over a range of 960 Km. Wide sense stationarity of the clutter seldom prevails over such a large region.

Therefore, there is a need to investigate methods, which offer the potential for reducing the computational complexity and the training data requirements for STAP in Gaussian and non-Gaussian interference scenarios. The work of Rangaswamy and Michels [18-20,24,25] provides a useful model-based parametric STAP method, which offers the potential for considerable reduction in training data support and computational complexity. In this method, the data processes are whitened through the use of multi-channel prediction error filters whose coefficients are chosen so as to match the inverse spectral characteristics of the interference. An important feature of this method is the lack of a need to form and invert the interference covariance matrix. Consequently, the limitation of $O(M^3)$ does not apply here. Furthermore, the use of a low model order filter enables significant reduction in training data support. The low model order approximation has been found to work well in a variety of simulated and real data scenarios. Figure 4 provides a brief overview of the model based parametric method using prediction error filters. The model based parametric method provides excellent performance in both Gaussian [25-27] and non-Gaussian interference scenarios [18-20 and references therein]. Other methods such as the cross spectral metric (CSM) [28], auxiliary vector method (AVM) [29], reduced dimension STAP [30], and multistage Wiener filter (MWF) [31] have been proposed for reducing the computational complexity and training data support requirements. A block diagram of these methods is shown in Figure 4. Additional reduced dimension STAP methods include element-space, beam-space pre-Doppler and post-Doppler techniques[32] and the principal components inverse (PCI) [33] and eigencanceller [34, 35] approaches. An important requirement of these methods is that the reduced-dimension weight vector span the clutter subspace and the signal subspace. A block diagram of reduced-rank STAP methods is shown in Figure 5.

Many of these methods are able to reduce only the computational complexity requirement since they still require that the estimated covariance matrix have full rank. Furthermore, the performance of the low rank methods

severely degrades in non-Gaussian interference scenarios. Another point of note is that most reduced rank STAP methods fail to maintain CFAR in both Gaussian and non-Gaussian interference scenarios. CFAR of reduced dimension methods is a subject of ongoing investigation.

IV CURRENT CHALLENGES AND OPEN PROBLEMS

Advances in system hardware permit the development of large arrays processing a large number of pulses in a CPI. Furthermore, operational scenarios get increasingly complex due to their highly composite nature leading to severe spatio-temporal clutter non-stationarity. Systems considerations such as bandwidth, frequency agility, internal clutter motion, aircraft crabbing, conformal arrays, spaceborne platforms, and bistatic geometry further exacerbate the clutter nonstationarity. Signal contamination of STAP training data leads to target cancellation. These effects call for efficient STAP methods to handle the following:

(i) Operation in non-stationary, heterogeneous clutter backgrounds (see [36] for details).
(ii) Reduced training data support for estimation of interference statistics and spectral characteristics (see [25-31,33] for possible approaches).
(iii) Performance analysis including operational effects-platform velocity, aircraft crab angle, channel mismatch, mutual coupling between the elements of the antenna array.
(iv)Computational cost reduction.
(v) CFAR in Gaussian and non-Gaussian interference scenarios using reduced dimension STAP.
(v) Robust STAP receiver design.
(vi) Dense target environments (see [15, 36, 37] for details).

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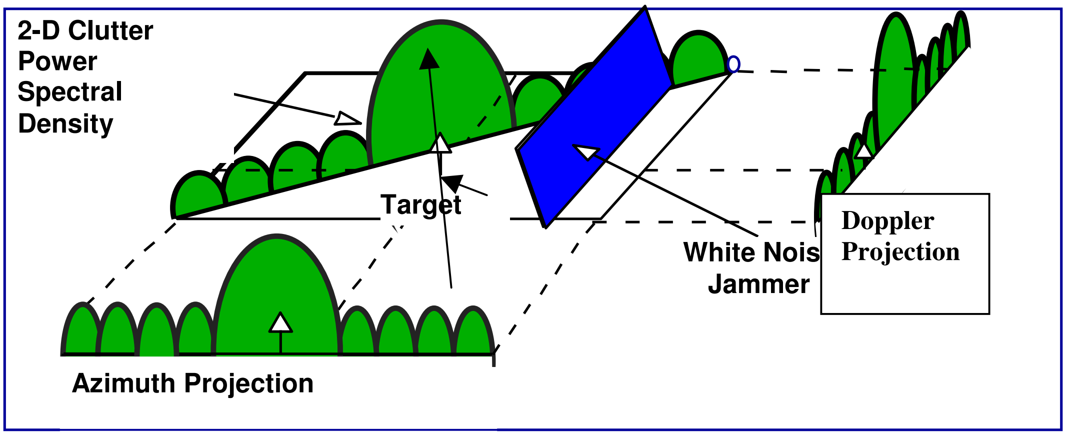

Figure 1: Power Spectrum from a Range Cell

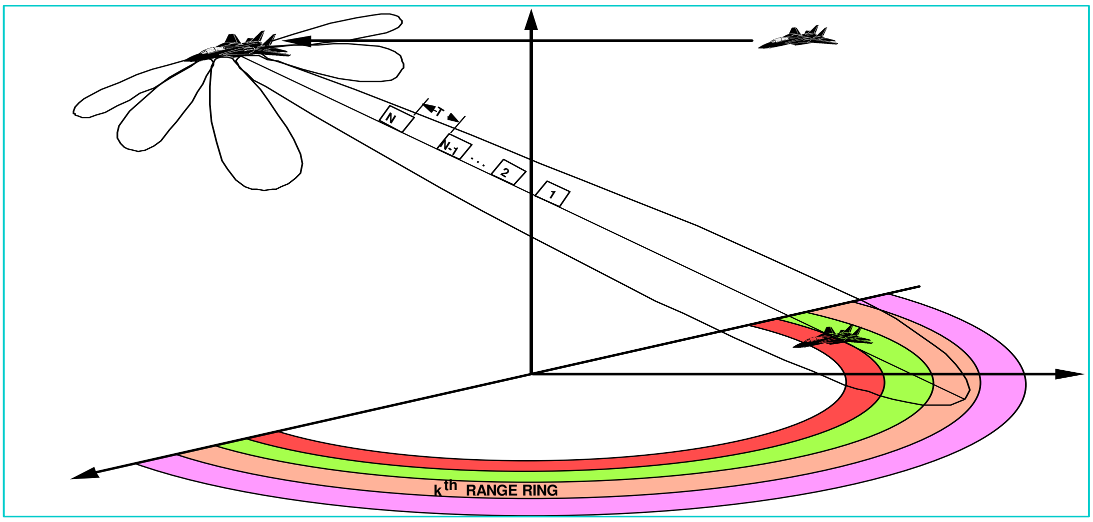

Figure 2: Airborne Radar Scenario

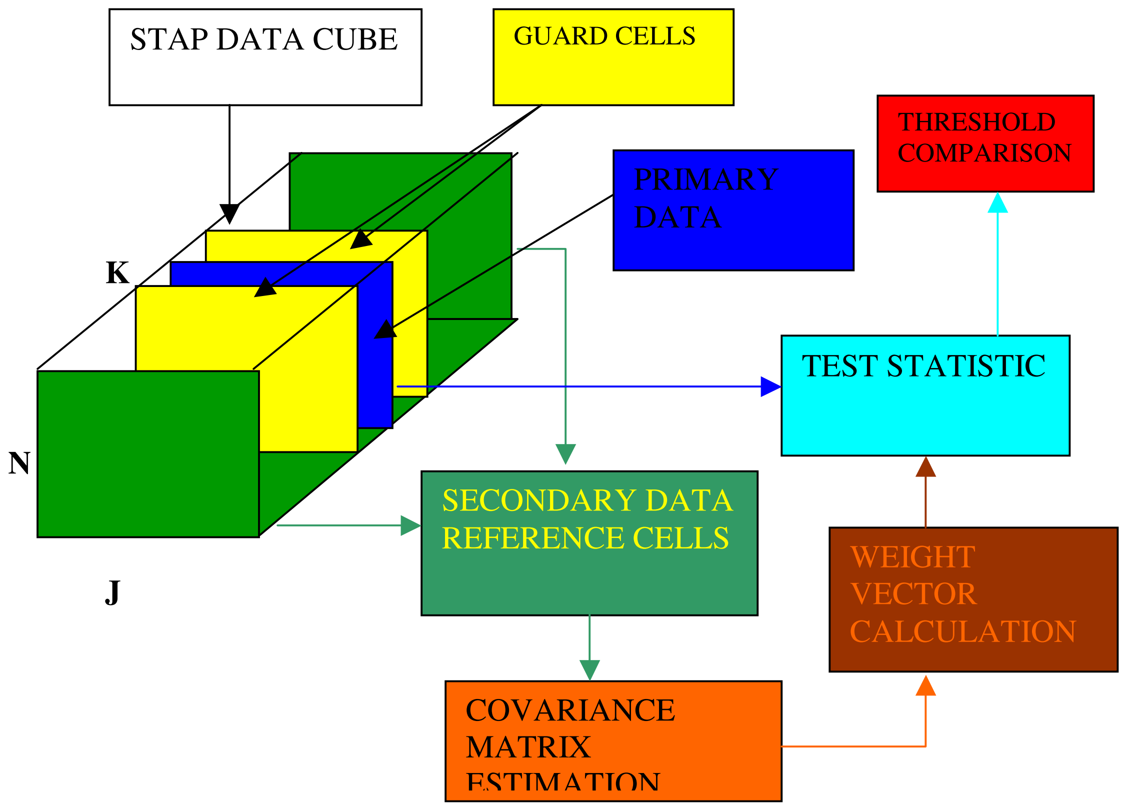

Figure 3: Classical STAP Processing

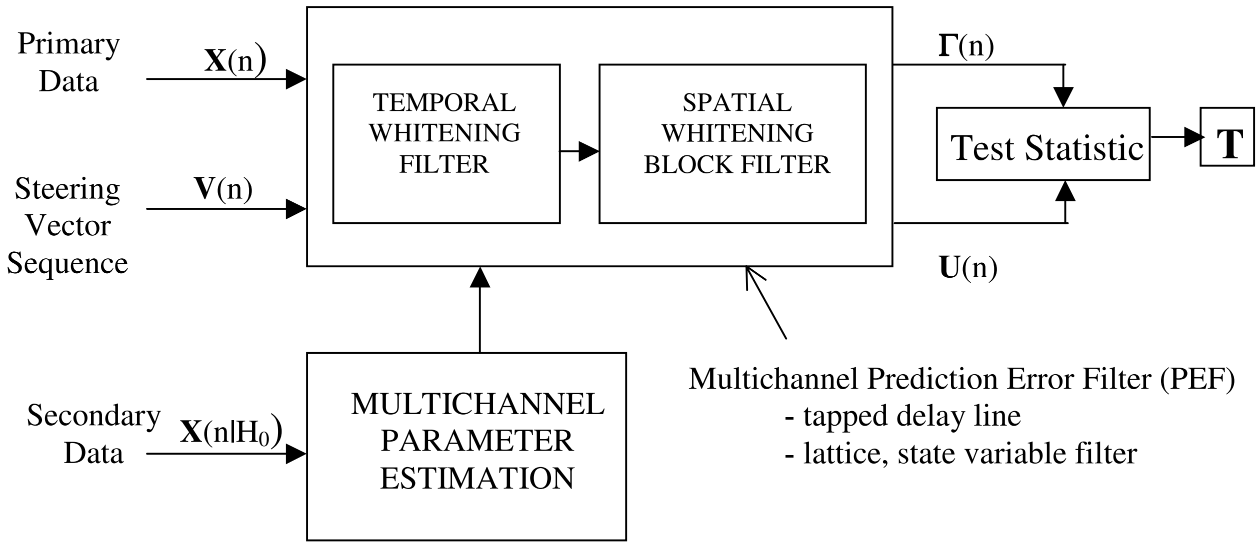

Figure 4: Parametric STAP

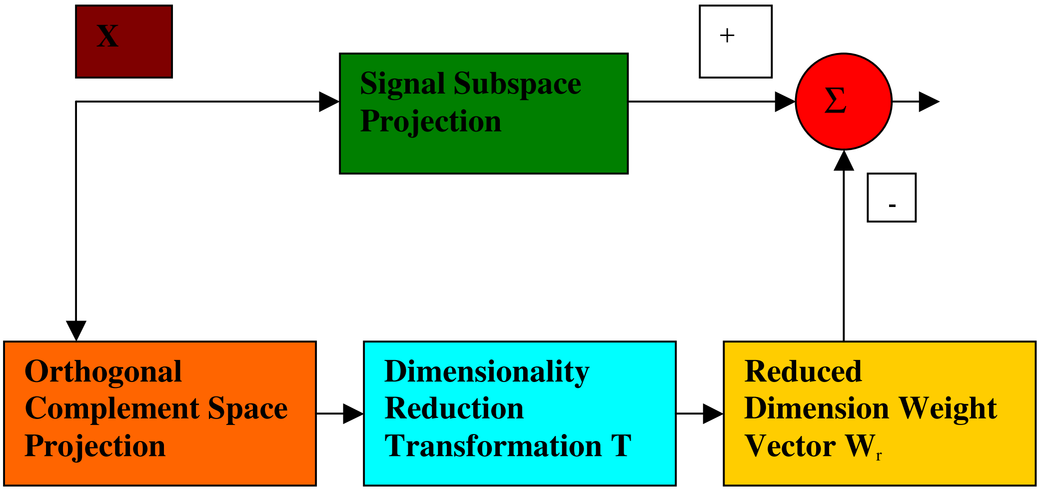

Figure 5: Reduced Rank STAP